

DIABETIC RETINOPATHY IDENTIFICATION USING EYE FUNDUS IMAGES ML USING PYTHON

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ABSTRACT:

Diabetic retinopathy may potentially lead to blindness without early detection and treatment. In this research, an approach to automate the identification of the presence of diabetic retinopathy from color fundus images of the retina has been proposed. Classification of an input fundus image into one of the three classes, healthy/normal, Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) has been achieved. Blood vessel segmentation from the input image is achieved by Gaussian filtering. An adaptive, input –driven approach is considered for the mask generation and thresholding is accomplished using local entropy. The processed image obtained is characterized by second order textural feature, contrast, in four different orientations- 0°, 45°, 90° and 135° and structural features namely, fractal dimension and lacunarity. The research incorporates a three layered artificial neural network (ANN) and support vector machines (SVM) to classify the retinal images. The efficiency of the proposed approach has been evaluated on a set of 106 images from the DRIVE and DIARETB1 databases. The experimental results indicate that this method can produce a 97.2% and 98.1% classification accuracy using ANN and SVM respectively invariant of rotation, translation and scaling in input retinal images as opposed to a fixed mask based on the matched filter method.

Keywords — Diabetic retinopathy, fundus images, Gaussian filtering, texture, contrast, fractal dimension, lacunarity, machine learning, artificial neural network, support vector machines.

I INTRODUCTION

- In the healthcare field, the treatment of diseases is more effective when detected at an early stage.
- *Diabetes is a disease that increases the amount of glucose in the blood caused by a lack of insulin.* It affects the retina, heart, nerves, and kidneys .
- **Diabetic Retinopathy (DR)** is a complication of diabetes that causes the blood vessels of the retina to swell and to leak fluids and blood .
- DR can lead to a loss of vision if it is in an advanced stage
- Retina regular screening is essential for diabetes patients to diagnose and

to treat DR at an early stage to avoid the risk of blindness .

- DR is detected by the appearance of different types of lesions on a retina image.

Diabetic retinopathy is a consequence to people affected by diabetes mellitus when glucose level is not kept in control [1]. It occurs as a result of an imbalance in the body's insulin level. The initial signs of the disease are expressed in the retinal vasculature as well as in the vitreous humor (gel surrounding the retinal blood vessels). The signs occur the form of hemorrhages, exudates, cotton wool spots (CWS) and microaneurysms (MA). The presence of these abnormalities leads to NPDR. The disease progresses into a severe stage known as PDR characterized by the abnormal growth of blood vessels (neovascularization) [2-4]. The distinction between a normal retina and a retina infected with diabetic retinopathy is shown in [3]. Color fundus images captured by a fundus camera provide the input for screening of diabetic retinopathy. Fig.1. illustrates a ray diagram of the image captured by a fundus camera .

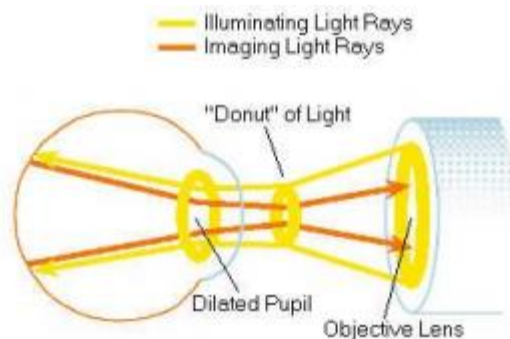


Fig. 1. Ray diagram of a monoscopic fundus image (from [5]).

At present, medical evaluation of retinopathy involves a detailed analysis of the color fundus images obtained by an ophthalmologist. The protocol followed is exhaustive and requires the support of four tests, namely, visual acuity, measurement of intra ocular pressure (IOP), gonioscopy and slit-lamp biomicroscopy [6]. It has been indicated that aforementioned tests are required since there is lack of evidence for a strong or substantial strength of support. The aim of this research is to automate the procedure to classify the input fundus image into one of the three classes by using image processing and machine learning techniques. Review of the literature indicates extensive research is underway pertaining to the classification of diabetic retinopathy by employing image processing techniques such as thresholding, mathematical morphology and filtering [7-9]. Verma, et al., classified different stages of diabetic retinopathy utilizing six features: area and perimeter of the red, green and blue layers of the original retinal images obtaining 91% accuracy [10]. The use of fractal characteristics to classify diabetic retinopathy provides an alternative approach to deal with nonEuclidian geometry of the retinal vasculature [11]. Agurto, et al., employed the use of textural features for retinal image analysis [12]. In this research, classification of diabetic retinopathy is performed on the original retinal images as well as the images obtained after blood vessel extraction. The features include contrast for four orientations: 0° , 45° , 90° and 135° , fractal dimension and two values of lacunarity. An artificial neural network as well as support vector machines

was utilized to perform classification. The remainder of the paper is organized as follows: Section II provides a description of the approach. The experimental results are presented in Section III while section IV discusses the conclusion and future work.

2. RELATED STUDY

The automatic diagnosis of diabetic retinopathy as a tool to support medical decisions has always been an engineering challenge⁵.⁶ In particular, machine learning techniques have been applied with some success to diabetic retinopathy diagnosis using as evidence individual sources of information^{7,8,9,10,11}.¹² Some abnormalities accumulate lipid residues causing serous leakage from damaged capillaries called exudates, that can be detected by examining eye fundus images, which is interpreted by a specialist ophthalmologist retina, which is often limited by the availability time thereof, and is susceptible to variability inter-observer.¹ Fundus eye image records and evaluates the retina of a patient based on the extraction and measurement of physical eye's characteristics. However, the prognosis of the disease with a preventive detection in diabetic subjects without retinopathy has not been explored yet. Automatic retinal image analysis has been considered as an important screening tool for early detection of eye diseases. Vandarkuhali and Ravichandran detected the retinal blood vessels with an extreme learning machine approach and probabilistic neural networks.⁷ Gurudath et al. worked with machine learning identification from fundus images with a

three-layered artificial neural network (ANN) and support vector machines (SVM) to classify retinal images.⁹ Also, Priyadarshini et al. studied clustering and classifications with data mining approaches to give some useful prediction applied to diabetic retinopathy diagnosis.¹¹ Machine learning techniques to detect the presence of exudates and healthy features in retinal images has been studied by others researchers: Fransens et al.,¹³ and Majerovic et al.,¹⁴ studied fuzzy and C means clustering and artificial neural networks to determine and classify exudates in an image, which shows the interest in using such tools or new methodologies such as deep learning to improve the results. The aim of the present work is to explore the LeNet¹⁵ convolutional neural network architecture to improve the classification of healthy and exudates images to support the correct diagnosis and postulate a preliminary prognosis of the disease. The remainder of this paper is organized as follows: First, in Section 2, we give an overview of the proposed method including data preprocessing and the convolutional neural network architecture.

3 METHODOLOGY

Preprocessing is a common stage in medical image processing. Its main goal is to enhance the characteristics of the image by applying a set of transformations that could help to improve performance in the following stages. The first step in this work is to extract the Region of interest (ROI) from the image as shown in Figure 2. Secondly, an oversampling strategy is used to both get

more samples artificially and help to prevent overfitting during training.

Cropping:

Computer-aided diagnosis (CADx) systems aim at classifying a previously identified ROI in the whole film image. This ROI can be obtained by a manual segmentation or automatically detected by a computer aided detection system. Because of lesions in e-optha dataset were manually segmented, we fixed the input size to ROIs of 48×48 pixels according to the average lesion size. With this in mind, ROIs can be easily extracted by taking the bounding box of the segmented region. Specifically, images were cropped to the bounding box of the lesions, where the lesion is centered without scaling and preserving the surrounding region. The condition to label a patch as a true exudate is that the intersection of the patch with an exudate region was greater than the 60% of the ROI. Otherwise, the patch was labelled as healthy patch.

Data augmentation

The expressiveness of neural network models, and particularly deep ones, comes mainly from the large number of parameters to learn. However, more complex models also increase the chance of over fitting the training data. Data augmentation is a good way to help to prevent this behaviour.¹⁶ Data augmentation is the process of artificially create new samples by applying transformations to the original data. In a classification problem, data augmentation makes sense because an exudate can be presented in any particular orientation. Thus,

the model also should be able to learn from such transformations. In particular, For each training image, we have artificially generated 7 new label-preserving samples using a combination of flipping and 90, 180 and 270 degrees rotation transformations.

4 RESULTS EXPLANATION

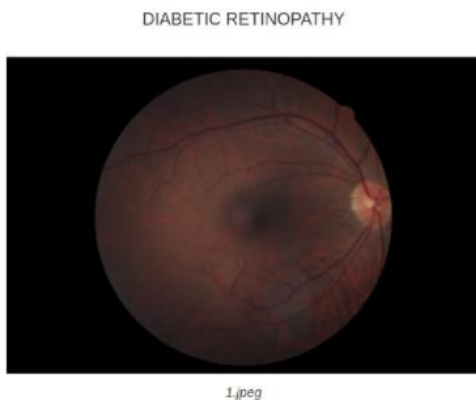
Results of the systematic exploration are reported. The best performance of the proposed model was obtained with a learning rate of 0.01 and a batch size of 64. We assessed the ability of the proposed model with the best parameters applied to an image from the test dataset that was randomly selected. Figure 3 presented an eye fundus image of 1440×960 pixels, the mask with the manual label by ophthalmologist and the mask generated by the proposed method. The CNN was modified at softmax layer with a threshold 0.75 to classify as an exudate values equal or greater than the threshold. Otherwise, it was classified as a healthy patch.



Fig.4.1. INPUT image.



Fig.4.2. Home page.



Predicted Label: **Infected**

Accuracy : **26.96 %**

Fig.4.3. OUTPUT results.

CONCLUSION

Experimental results showed that the CNN model is highly effective to detect exudate in eye fundus images. The results clearly improved the results reported by the baseline method.¹⁷ The main advantage of the proposed method is that it receives as input the raw image and learns to extract the most discriminative features. A drawback of representation learning methods is that they are datahungry, i.e. they require large data sets for training. This problem was overcome by using a data augmentation strategy allowed us to grow the training data to eight

times its size with a consequently improving in performance. These results are consistent with other works that have reported similar improvements when applying convolutional neural networks to other types of medical images. The detection of earliest clinical sign in diabetic retinopathy such as exudates may improve the disease diagnosis and the risk stratification of diabetic subjects without diabetic retinopathy. This work is a first step on building highly accurate automatic diagnostic tools that support the work of ophthalmologists. This research showed good preliminary results in exudate detection. Its application to detection of microaneurysm and other signals and symptoms of diabetic retinopathy is the subject of our future work.

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